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Jill Cetina
Office of Financial Research
jill.cetina@ofr.treasury.gov

Mark Paddrik
Office of Financial Research
mark.paddrik@ofr.treasury.gov

Sriram Rajan
Office of Financial Research
sriram.rajan@ofr.treasury.gov

Stressed to the Core: Counterparty Concentrations and Systemic Losses in CDS Markets*

Jill Cetina†
Mark Paddrik‡
Sriram Rajan§

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Abstract

Supervisory stress testing to date has focused on the resiliency of large banks to withstand the direct effects of a credit shock. Using data from Depository Trust & Clearing Corporation (DTCC), we apply the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) supervisory scenarios to evaluate the default of a bank's largest counterparty. We find that indirect effects of this default, through the bank's other counterparties, are larger than the direct impact on the bank. Further, when taken as a whole, the core banking system has a higher concentration to a single counterparty than does any individual bank holding company. Under the 2015 stress, the banking system's counterparty credit concentration is high and corresponds in diversity to a market with just over three firms. Our results are the first to evaluate the credit derivatives market under stress and also underscore the importance of a macroprudential perspective on stress testing.

Keywords: Credit default swaps, stress testing, systemic risk, financial networks, counterparty exposure, contagion

JEL Classification Numbers: D85, G01, G13, G20, L14

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†Office of Financial Research, United States Department of Treasury, email: Jill.Cetina@ofr.treasury.gov.

‡Office of Financial Research, United States Department of Treasury, email: Mark.Paddrik@ofr.treasury.gov.

§Office of Financial Research, United States Department of Treasury, email: Sriram.Rajan@ofr.treasury.gov.

1 Introduction

Supervisory stress tests provide important insights into the resilience of banks under distressed economic and financial conditions. The Comprehensive Capital Analysis and Review (CCAR) conducted annually by the Federal Reserve, aims to identify the extent and source of capital losses at the largest U.S. bank-holding companies (BHCs) as well as evaluate firms' capital planning abilities. Firms stress their banking and trading books under instructions from the Federal Reserve regarding stresses for debt securities based on credit rating bucket, among other break outs. This work provides valuable insight about the first-order effects of a credit shock on large U.S. banks' capital adequacy. However, such estimates could have a downward bias as they don't reflect how the counterparties of the BHC might be adversely affected in stress.

The aggregate impact of a counterparty's default is a potential systemic risk concern. The failure of a highly interconnected counterparty, such as American International Group, Inc. (AIG) in 2008, could have large and consequential effects and may be difficult to estimate. In 2014, the Federal Reserve instituted under CCAR a counterparty default scenario, as part of stress testing BHCs' trading books, requiring individual BHCs to attribute sources of loss and gain to their counterparties. Each BHC's largest trading counterparty is determined by net stressed profit and loss (P&L), estimated by revaluing exposures and collateral using the severely adverse supervisory scenario for the trading book. Across the trading book (including derivatives, reverse repo and securities financing agreements), the counterparty whose positions experience the largest loss to a BHC after the shock is assumed to fail, increasing the BHC's losses. [1]

We analyze the question of how to incorporate counterparty risk exposures in supervisory stress tests. We conduct an analysis of the CCAR stress test by using credit default swap (CDS) markets as a proxy for banks' trading books. Credit derivatives exposures were at the core of the 2008-09 financial crisis, and while the market has contracted substantially since 2008, it still is the source of sizable risk-taking among market participants. Transactional data provided to the Office of Financial Research (OFR) from the Depository Trust & Clearing Corporation (DTCC) gives data on standardized confirmed CDS transactions involving U.S. entities and sufficient contractual information to re-estimate the P&L of counterparties based on the severely adverse supervisory scenario

[1] While there are prudential limits on counterparty risk exposures in bank regulation, these limits are based on current exposures, not exposures in a stress scenario.

for all U.S. entities. We use DTCC information with the Federal Reserve's CCAR stresses that vary across asset classes, ratings buckets, and debt priority, to obtain an analogue to the submissions the Federal Reserve receives from the six U.S. BHCs required to conduct the trading shock portion of CCAR.[2] We refer to these banks as being in the *core* financial system to emphasize their focal role in the financial system and, indeed, in the CCAR trading shock exercises. Other commercial and investment banks, hedge funds, asset managers, insurance companies, and other market participants constitute what we shall refer to as the peripheral financial system, a nomenclature which distinguishes them as being distinct from the core but does not imply their role in the financial system is unimportant.

Our research yields important insights about potential estimation bias in evaluating banks' counterparty risk exposures in supervisory stress tests. The paper proceeds as follows. Section 2 presents background on stress testing of counterparties using networks and how it is currently performed in CCAR. Section 3 describes the data used in the analysis. Section 4 describes the methodology used to price and mark-to-market portfolio positions for all CDS counterparties, consistent with the CCAR severely adverse stress scenarios for 2013, 2014, and 2015, respectively. Section 5 provides summary statistics of the CDS market before and after incorporation of the stress test scenarios. Section 6 analyzes the P&L associated with the stress of a BHC's largest counterparty, impacts on the BHC's other counterparties, concentration risks to the core banking system, and consideration of losses to the rest of the financial system. A final section summarizes the paper and concludes.

2 Background

The desire to restore confidence in the banking system as well as the failure to foresee the events of 2007 and 2008 has led to a strengthened regulatory approach to stress testing banks' capital risk, beginning with the Supervisory Capital Assessment Program (SCAP) in 2009 (Hirtle et al. (2009)). The SCAP subjected the 19 largest U.S. BHCs to a uniform stress test designed by regulators; companies that failed the SCAP test were required to raise new capital or accept relatively expensive government capital. The SCAP played a crucial role in turning around the

[2]The six BHCs are: Bank of America Corp., Citigroup Inc., Goldman Sachs Group, Inc., JPMorgan Chase Co., Morgan Stanley, and Wells Fargo & Co.

financial crisis in the United States by subjecting the banks' portfolios to stressful assumptions and requiring them to raise and hold capital sufficient to withstand a severe credit shock.

2.1 Supervisory Stress Testing

SCAP was superceded by the Comprehensive Capital Adequacy Review (CCAR) in 2011 (see Federal Reserve (2015)). The CCAR process includes the collection of granular balance sheet and income statement data from each BHC. Banks' and Federal Reserve models then use these data to evaluate the implications of stress scenarios. In addition to estimating credit losses, the BHCs and the Federal Reserve apply shocks to different risk factors to arrive at P&L estimates for each bank's trading book.

Estimates of the six largest BHCs' trading losses were further refined in the 2014 CCAR with the Federal Reserve's introduction of a counterparty default scenario. This scenario evaluates the resilience of a BHC to withstand the loss of its single largest trading counterparty. The scenario defines the largest trading counterparty as the one that represents the largest source of gains to the BHC. (Upon a sudden and unexpected default, this counterparty equivalently represents the largest source of loss.) Sources of counterparty gains come from derivatives and securities financing activities such as securities lending and reverse repurchase agreements. Each BHC's largest counterparty is determined by net stressed gains to the BHC, which are, in turn, estimated by revaluing exposures and collateral using the severely adverse scenario for the trading book. The counterparty whose positions represent the largest gain to the BHC under stress is assumed to fail. This paper uses this approach as a benchmark to examine the distribution and concentration of such losses based on CCAR's severely adverse scenarios for the trading book from 2013 to 2015. [3] Because DTCC data allow one to evaluate the effect of the scenario on the entire CDS market, we are able to measure, in addition to direct impacts to the BHC, the indirect impacts to other BHC counterparties, the core banking financial system, and the peripheral financial system comprised of firms outside the stress test.

[3]The risk factors we apply to the CDS data are from Federal Reserve worksheets provided to the CCAR participants. The risk factors shocks for these years are in Tables 2, 3, 4

2.2 Networks and Stress Testing

Prior to the 2008-09 crisis, financial regulators placed less effort on assessment of system-wide characteristics of networks and risks within them (Haldane and May (2011)). Rather their primary focus had been dedicated to the assessment of individual institutional risks. As a result of the crisis, however, the importance of systemic risk assessment has grown. First recognized by Eisenberg and Noe (2001) in the application of network models, systemic risk assessment is distinct from assessment of individual banks (Haldane et al. (2009)).

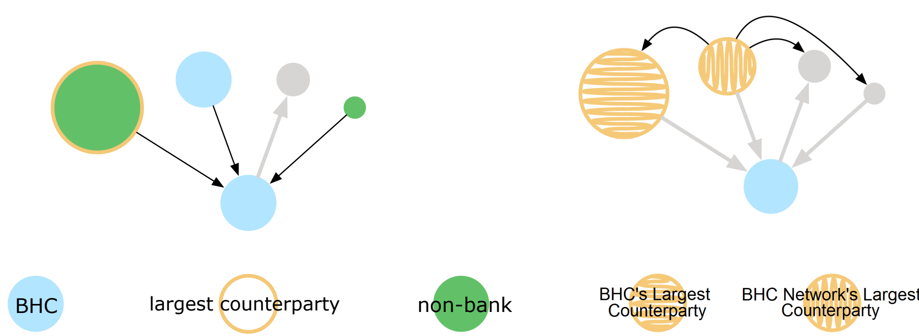
The transition has led to more network-centric approaches of systemic risk monitoring and measurement. Stress-testing assessment techniques using network measures (Bech and Atalay (2010); Battiston et al. (2012)) and models like that of Gai and Kapadia (2010), which incorporate securities and balance sheet connections and identify channels for contagion, have been growing areas of research. Such insights into evaluating contagion have assisted regulators, researchers, and market participants, interested in evaluating financial stability risk.

Even as the crisis revealed how more granular information about exposures were needed, progress remains slow on gathering complete data on various markets, such as secured funding markets, to be able to analyze the full network. As construction of a financial network requires complete information, there are a number of papers which implement methods of network reconstruction using partial data (Basel Committee on Banking Supervision (2015), Baral and Fique (2012), Drehmann and Tarashev (2013), Hałaj and Kok (2013), Mastromatteo et al. (2012)). However, while network methods have not been applied so far in supervisory stress tests in the United States, there have been examples of the application of network methods in supervisory stress tests elsewhere (Bank of Korea (2012), European Central Bank (2013) and Anand et al. (2014)). This paper is one of the first to consider the implications of the network structure for stress testing U.S. banks with a nearly complete dataset from DTCC on the U.S. CDS market as a result of post-crisis reforms.

2.3 Concentration Risk

Bank supervisors have long known that credit concentrations can increase the risk of a firm's failure. However, supervisory methods for evaluating credit concentrations historically have focused on a bank's direct exposures to other institutions. While supervisory awareness of issues such as correlation of exposures and the risks of indirect exposure in securitizations have increased since the crisis (Comptrollers Handbook, ACOC (2011)), supervisory guidance has yet to consider the potential risks arising from the indirect effects of credit loss through network propagation mostly due to data limitations and computational complexity. Specifically, indirect effects address the potential for contagion to a bank's other counterparties from the failure of one counterparty. Are there hidden indirect concentrations in the network beyond the direct exposures that supervisors can readily observe? Are these effects small or material enough to change our understanding of where a bank's credit concentration lies?

Figure 1: Direct and Indirect Counterparty Influence on a BHC



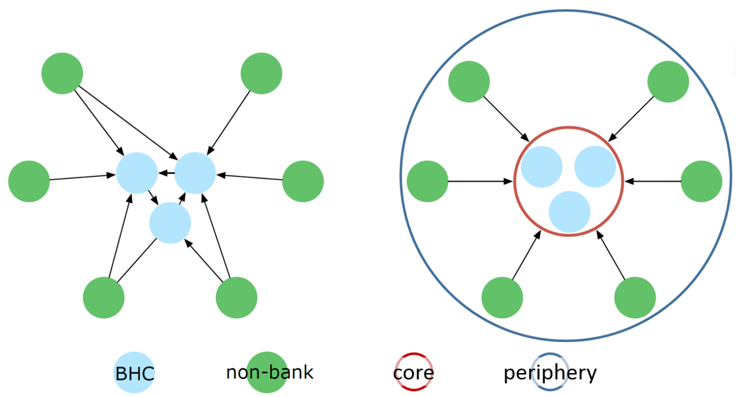
(a) Direct Loss (b) Indirect Loss

Source: Authors

Figure 1 depicts the two different degrees of concentrations we are concerned with. The CCAR stress scenario looks exclusively at the direct loss concentration risk, and does not consider the ramifications of indirect losses that may come through a shared counterparty, who is systemically important. A few papers have applied network propagation methods to empirical data to evaluate the general equilibrium effects of a stress (Martinez-Jaramillo et al. (2014) and Battiston et al. (2012)) on counterparties, though limited by the degree of the P/L knowledge of the firms.

Traditionally the manner in which concentrations has been measured is through the Herfindahl index. However, when considering concentration across a network there is a need to differentiate the implications it has on the system's loss profile (Capponi et al. (2014)). As the CDS market has a strong core-periphery network of counterparties, where market participants generally buy and sell protection through U.S. BHC and foreign banking organizations (FBOs), the difference in concentration risks that BHCs face individually relative to what they face as a system may be very different, as depicted in Figure 2.

Figure 2: Core and Periphery Losses



Source: Authors

3 Data

This study uses data from DTCC concerning CDS exposures of market participants and identifies their roles as protection sellers or buyers. Each exposure is further described by contractual information such as the reference entity source of credit risk, trade date, termination date, and notional amount of the contract. We integrate this contractual information with credit spread term structure and recovery rate quotes from Markit Group Ltd. Markit differentiates quotes by the International Swaps and Derivatives Association's (ISDA) default documentation clause, seniority of the reference obligation, and base currency.

We observe positions on individual entities (*single name* reference entities), indices, and tranches. Because the notional of the last category represents something on the order of 1 percent of total outstanding, we disregard this source of risk. For the purposes of pricing, we must disaggregate indices to single-name equivalents, which is also performed using information from Markit. We are able to identify index constituents and weights as of any given date and take into account index defaults and revisions.

Table 1: Aggregate Statistics

As-of-date	# Counterparties	# Positions	# Reference Entities
11/09/2012	1060	6,282,128	4297
10/11/2013	985	7,273,913	3651
10/03/2014	959	6,389,129	3173

Success Rate of Marking Positions	
Total # of Pricing Dates:	3703
Count	State
3,002,847	FAIL
16,964,019	SUCCESS

Source: Authors' calculations using DTCC data
Note: We evaluate 6-7 million positions, involving roughly 1000 counterparties, and 3,000-4,000 reference entities. Of 19.9 million positions over all pricing dates, we are able to mark 16.9 million successfully.

Some information is not included in the DTCC data, yet is required for revaluing CDS contracts under CCAR shocks. First, we make assumptions about the documentation clauses and terms of default that are referenced in CDS contracts. For each DTCC position we observe, we search Markit to identify a CDS quote, in the following order of preference: XR, MR, XR14, MR14, CR, CR14, MM, MM14. This ordering represents the observed frequency of documentation clauses seen in Packer et al. (2005). XR is a contract clause that excludes restructuring events as a trigger of default. MR and MM contracts permit some forms of restructuring. CR contracts permit full restructuring. Contracts with the number "14" appended follow the same conventions and also relate to contracts under ISDA's new 2014 definitions. Additional data that we do not receive from DTCC but required to reprice the CDS positions are the reference entity obligation seniority and base currency, which we assume to be senior and U.S. dollars, respectively.

The data OFR receives from DTCC does not contain positions that are solely between foreign counterparties on foreign reference entities. However, the data do contain transactions between U.S. and foreign counterparties, and transactions between foreign firms on U.S. reference entities.

The DTCC data contain a field that indicates the firm with which an individual counterparty is affiliated. We use this field of firm to eliminate intra-affiliate positions and to arrive at a consolidated view of a firm's risk.

Table 1 provides gross statistics on the data used in this paper. We conduct 2013, 2014, and 2015 stress tests using reported positions as of 11/09/2012, 10/11/2013, and 10/03/2014, respectively.

The number of counterparties during these years is roughly 1,000 and they enter into between 6 and 7 million positions on between 3,173 and 4,297 reference entities. On an aggregate basis, we attempt to value 19.9 million positions of which approximately 15 percent, by count, cannot be marked (see Table 1). This is most often because of missing Markit quotes, or in fewer instances, an inability for other reasons to compute hazard rates using the technique in Section 4.

4 Generation of Stressed Counterparty Exposures

Stress testing the CDS market is a computationally and data intensive task that involves a number of steps. Broadly, we develop a compendium of single-name and index positions and corresponding contractual information needed for marking-to-market each counterparty's individual exposures. We track position marks at each CCAR valuation date to generate P&L. In the following sections, we first discuss how hazard rate curves are generated, then document how positions are marked to market, and finally describe the aggregation of P&L.

4.1 Credit Default Swap Valuation

We value credit default swaps by using a well-accepted hazard rate approach, as given in Luo (2005). The premium leg of the CDS is the discounted expected value of CDS premia s_T receipts through some time horizon T, so long as default time τ does not come earlier.

$$\begin{aligned} V_{prem} &= \mathbb{E}\left[\sum_{i=1}^{N} exp\left(-\int_0^{t_i} r_s ds\right) \mathbb{I}_{\tau > t_i} s_T\right] \\ &= s_T \left[\sum_{i=1}^{N} exp\left(-\int_0^{t_i} (r_s + \lambda_s) ds\right)\right] \\ &= s_T \left[\sum_{i=1}^{N} Z(0, t_i) S(0, t_i)\right] \end{aligned} \tag{1}$$

The last expression discounts the spread by the sum of discount factors, each of which pertains to a premium receipt date. Each discount factor is expressed in two components, one which relates to interest rate risk and another to credit risk. $Z(0, t_i)$ is a riskfree discount factor which can be readily computed from swap rates. $S(0,t_i)$ is the credit-risky default component, or cumulative probability of survival to time t_i.

The pay leg (also called default leg) is the expected realization of loss, $(1-R)$, with R as the recovery rate of the defaulted underlying, given that default time τ comes before horizon T.

$$\begin{aligned}
V_{pay} &= \mathbb{E}\left[exp\left(-\int_0^\tau r_s ds\right)\mathbb{I}_{\tau\leq T}(1-R)\right] \\
&= (1-R)\int_0^T \mathbb{E}\left[\lambda_t exp\left(-\int_0^t (r_s+\lambda_s)ds\right)\right]dt \\
&= (1-R)\int_0^T \mathbb{E}\left[exp\left(-\int_0^t r_s ds\right)\right]\mathbb{E}\left[-\frac{d}{dt}exp\left(-\int_0^t \lambda_s ds\right)\right]dt \\
&= (1-R)\int_0^T Z(0,t)\left(-\frac{d}{dt}S(0,t)\right)dt
\end{aligned} \tag{2}$$

The second expression follows from the proof of 3.3 and 3.4 in Lando (1998). We shall use the final expression from this point.

4.2 Implementation

Consistent with CDS market convention, we use a daycount convention of quarterly payments, paid upon International Monetary Market (IMM) dates. In subsequent notation, the daycount fraction is represented by Δ_i and roughly equals 0.25 for any period i. For computation of riskfree discount factors $Z(0,t_i)$, we obtain 3-month through 30-year swap rates from Bloomberg L.P.

We allow for the possibility CDS pay accrued premia on default to the protection seller, ie. that when a default occurs inter-period, CDS premia to the protection seller are pro-rated to the time of default. In the expression for the premia leg above, $S(0,t_i)$ is survival probability to period i. However, should the credit default between $i-1$ and i and accrued premia are to be paid, we redefine $S^*(0,t_i) = (1-\alpha)S(0,t_i) + \alpha S(0,t_{i-1})$. We assume $\alpha = 0.5$ (ie, that a default occurs at the interperiod haflway point).

4.3 Bootstrapping Credit Curves

Using daycount fractions and accrued premia conventions as discussed above, we rewrite Equation 2 through term T_1. We make explicit the dependence of the premium leg through T_1 on a corresponding hazard rate, λ_1:

$$V_{prem}^{0\to T_1}(\lambda_1,\ s_{T_1}) = s_{T_1}\sum_{i=1}^{N_1} Z(0,t_i)\Delta_i\left((1-\alpha)S(0,t_i)+\alpha S(0,t_{i-1})\right) \quad (3)$$

We approximate the differential $-\frac{d}{dt}S(0,t) = S(0,t_{i-1}) - S(0,t_i) = P(0,t_i) - P(0,t_{i-1})$ and can similarly discretize the pay leg as

$$V_{pay}^{0\to T_1}(\lambda_1) = (1-R)\sum_{i=1}^{N_1} Z(0,t_i)\left(P(0,t_i) - P(0,t_{i-1})\right) \quad (4)$$

λ_1^* is the solution that sets CDS payment and premia legs to equality at inception, ie. $V_{contract}^{0\to T_1}(\lambda_1^*,\ s_{T_1}) = V_{pay}^{0\to T_1}(\lambda_1,\ s_{T_1}) - V_{prem}^{0\to T_1}(\lambda_1) = 0$.

We use the methodology from Luo (2005) to express the subsequent stage of the bootstrap technique. For any reference entity, we have a term structure of fair-value spreads $\left\{t_1\colon s_1,\ t_2\colon s_2,\ t_3\colon s_3,\ \ldots\ t_n\colon s_n\right\}$. The bootstrap technique generates hazard rates $\left\{(0,t_1]\colon \lambda_1^*,\ (t_1,t_2]\colon \lambda_2^*,\ (t_2,t_3]\colon \lambda_3^*,\ \ldots\ (t_{n-1},t_n]\colon \lambda_n^*\right\}$ that establish fair value. Upon having computed the hazard rate from inception through T_1, the second stage is to compute λ_2^*, given λ_1^*. Any subsequent stage computes λ_m^*, given $\boldsymbol{\lambda_{m-1}^*} = \left\{\lambda_1^*,\ \lambda_2^*,\ \ldots\ \lambda_{m-1}^*\right\}$. N_m is the index of the mth IMM payment period for the CDS contract. In general form, the conditional premia and payment legs are given as follows:

$$\begin{aligned}&\mathrm{V}_{prem}^{0\to T_m}(\lambda_m,\ s_{T_m};\ \boldsymbol{\lambda_{m-1}^*})\\ &= s_{T_m}\left\{C(\boldsymbol{\lambda_{m-1}^*}) + \textstyle\sum_{i=N_{m-1}+2}^{N_m} Z(0,t_i)\Delta_i[P(t_{N_m+1}) - ((1-\alpha)P(t_i) + \alpha(P(t_{i-1}) - P(t_i)))]\right\}\end{aligned}$$

$$\begin{aligned}&V_{pay}^{0\to T_m}(\lambda_m;\ \boldsymbol{\lambda_{m-1}^*})\\ &= A(\boldsymbol{\lambda_{m-1}^*}) + \textstyle\sum_{i=N_{m-1}+2}^{N_m} Z(0,t_i)(P(t_i) - P(t_{i-1}))\end{aligned}$$

λ_m^* is the solution that sets the CDS of term T_m to fair value, given the hazard rate observed over $(0, T_{m-1})$, ie. $V_{contract}^{0\to T_m}(\lambda_m,\ s_{T_m};\ \boldsymbol{\lambda_{m-1}^*}) = V_{pay}^{0\to T_m}(\lambda_m; \boldsymbol{\lambda_{m-1}^*}) - V_{prem}^{0\to T_m}(\lambda_m,\ s_{T_m};\ \boldsymbol{\lambda_{m-1}^*}) = 0$. $C(\boldsymbol{\lambda_{m-1}^*})$ and $A(\boldsymbol{\lambda_{m-1}^*})$ are functions of known hazard rates, parameterized in prior steps of the bootstrap.

4.4 Portfolios of Single Name Equivalents

For the purposes of marking portfolios of indices to market, we disaggregate index positions to their single-name equivalents in the manner described by Siriwardane (2015) in Section 2. We use eXtensible Markup Language (XML) index decompositions available from Markit's website, which contain a history of all index vintages and their compositions at various points in time.

Each Markit credit index is described by its series and version. A series may have one or more versions. An index series factor, f_i is defined for every version i as $f_i = 1 - \frac{D_{i-1}}{N}$, where D_{i-1} is the number of defaults for an index series version i in $1, 2, 3$ .... $D_0 = 0$, so $f_1 = 1$. The weight of a constituent within a version must be computed as of a valuation date of interest and is a function of the index composition as of the date the position was established (trade date). In general, the index composition at the trade date may not be its composition at inception. The current weight $w_i(c)$ for index version i of a constituent c whose inception index series weight is $w_0(c)$ is given as

$$w_i(c) = \frac{w_0(c)}{f_i} \tag{5}$$

As an example, an index with 43 original constituents at inception would have a per-constituent weight of $w_1(c) = \frac{\frac{1}{43}}{1} = 0.02326$. Version 2 of the index would have a per-constituent weight of $w_2(c) = \frac{\frac{1}{43}}{0.95348} = 0.02439$. The per-constituent weight is scaled by the notional value of the index position to arrive at the effective single-name notional equivalent. We perform all calculations in this paper on single-name equivalent notional positions.

4.5 Marking Positions to Market

While credit curves are bootstrapped to market rates, positions are marked against fixed coupon spreads paid on CDS contracts. However, survival and default probabilities used in valuation arise from market rates, as discussed in Beumee et al. (2009). It is useful to incorporate the counterparty flows in the description of the net present value (NPV), i.e. that x sells protection to y. x is long the premium leg and short the payment leg; stated alternatively, x writes the payment leg, while y writes the premium leg. Incorporating counterparty flows, suppressing some earlier notation, and taking into account a fixed coupon c, we express $V_{prem}^{0\to T_m}(\lambda_m{}^*,\ c;\ \boldsymbol{\lambda_{m-1}}^*)$ as $V_{prem}^{x}(c,\ \boldsymbol{\lambda})$ and similarly the payment leg as $V_{pay}^{y}(\boldsymbol{\lambda})$. To indicate that the legs are computed at trade inception t_0, we describe the hazard rate environment as $\boldsymbol{\lambda^0}$. The NPV of a corresponding swap position of \$$N$ is given as:

$$NPV^{x\to y}(N, \boldsymbol{\lambda^0}, c) = N\left[V^x_{prem}(c,\ \boldsymbol{\lambda^0}) - V^y_{pay}(\boldsymbol{\lambda^0})\right] \tag{6}$$

The swap at a subsequent as-of-date t_n is described by:

$$NPV^{x\to y}(N, \boldsymbol{\lambda^n}, c) = N\left[V^x_{prem}(c, \boldsymbol{\lambda^n}) - V^y_{pay}(\boldsymbol{\lambda^n})\right] \tag{7}$$

The mark-to-market is the difference between the NPV at time t_n and initial time t_0.

$$MtM^{x\to y}(N, \boldsymbol{\lambda^0}, \boldsymbol{\lambda^n}, c) = NPV^{x\to y}(N, \boldsymbol{\lambda^n}, c) - \frac{1}{Z(t_0, t_n)}NPV^{x\to y}(N, \boldsymbol{\lambda^0}, c) \tag{8}$$

[Table 2] [Table 3] [Table 4]

Under CCAR, credit-risky securities are subject to a variety of shocks absolute and proportional to credit spreads, or proportional to market value. Shocks are prescribed across geographies, credit categories (e.g, loans; municipal, state, and sovereign credit; and corporate credit), and ratings classes. The extent to which shocks are specified varies through years and reflects the Federal Reserve's views on current risks for bank solvency. Using the CCAR trading shock stresses prescribed in Tables 2, 3, 4 for 2013, 2014, and 2015 we can compute the NPV under stress.

$$MtM^{x\to y}(N, \boldsymbol{\lambda^0}, \boldsymbol{\lambda^{shock}}, c) = NPV^{x\to y}(N, \boldsymbol{\lambda^{shock}}, c) - \frac{1}{Z(t_0, t_n)}NPV^{x\to y}(N, \boldsymbol{\lambda^0}, c) \tag{9}$$

and the change in NPV as a consequence of the stress

$$\Delta MtM^{x\to y} = MtM^{x\to y}(N, \boldsymbol{\lambda^0}, \boldsymbol{\lambda^{shock}}, c) - MtM^{x\to y}(N, \boldsymbol{\lambda^0}, \boldsymbol{\lambda^n}, c) \tag{10}$$

5 Aggregate Statistics

5.1 CDS Sectors

In Table 5, we summarize aggregate P&L impact from the perspective of all sellers of CDS protection on a gross basis with regards to the CCAR stress among mutually exclusive categories of reference entities. Specifically, we do not net individual counterparties' gains against losses to arrive at this aggregate figure. Categories of reference entities include: advanced economies and emerging markets these include investment-grade and sub-investment grade non-financial corporate credit. Additionally, sovereign credit and exposures to U.S. financials and non-U.S. financials are broken out separately.

We report aggregate seller profits (losses) using observed history (i.e., we assume no shock) on the trading stress dates for 2013, 2014, and 2015. The stressed case applies CCAR's stress scenario for each year and revalues positions appropriately. Three factors can drive the variation in P&L across the CCAR periods: 1) initial value of the position; 2) effect of CCAR stress; and 3) notional size of the position. As the goal of this paper is not to conduct a cross-sectional comparison of CCAR results, we limit the observations derived from this exercise to a few points. First, the mark-to-market loss on U.S. entities' CDS positions is the largest for non-U.S. financial and sub-investment grade advanced economy corporate reference entities, although losses decline over the successive CCAR tests. Second, a source of variation in the stress tests has been the P&L impact of sovereign exposures, which was most pronounced in 2014.

[Table 5]

5.2 Counterparty Exposures

We observe over 2013 to 2015 that BHCs and FBOs, classified by DTCC as dealers, evolve from being net sellers to net buyers of CDS protection (Table 6). The average BHCs and FBOs as of the most recent CCAR stress test was a net buyer of some $1.7 billion of notional protection, while the average non-BHC and non-FBO was a net seller of $49 million of notional. CCAR may motivate banks to reduce their provision of credit protection in the CDS market to minimize their losses under CCAR's trading shock. However, the adoption of the enhanced supplemental leverage ratio (SLR) could also encourage U.S. banks to reduce their CDS exposures. The SLR requires covered BHCs to hold 5 percent of capital against their total exposures, including derivatives.[4] However, as illustrated in Table 6, the kurtosis and standard deviation of net notional indicates that some non-bank sellers of CDS protection have large net long positions.

[4] In the United States, the enhanced supplemental leverage ratio applies to BHCs with total exposures in excess of $250 billion or with international exposures in excess of $10 billion.

[Table 6]

Looking from the perspective of the stressed P&L data, we see a similar pattern in the distributions. The kurtosis and standard deviation implies a few CDS protection sellers could pose outsized counterparty credit risk to banks in stress and suggests that stressed risks in the U.S. CDS market remain fairly concentrated post-crisis.

[Table 7]

6 Default of the Largest Counterparty

6.1 Firm-Level Direct Impacts

The impact of any counterparty p to a BHC can be measured by taking into account the mark-to-market (MtM) change across all protection sales of the BHC to p and protection purchases of the BHC from p, respectively:

$$\Delta V_p^{bhc} = \sum_{\substack{j \in \\ Sales}} \Delta MtM_j^{bhc \to p} + \sum_{\substack{k \in \\ Purchases}} \Delta MtM_k^{p \to bhc} \tag{11}$$

The CCAR largest-counterparty default scenario is focused on *gains* to the BHC foregone upon counterparty p's default. We construct a sequence of counterparties whose default would result in a loss to the BHC:

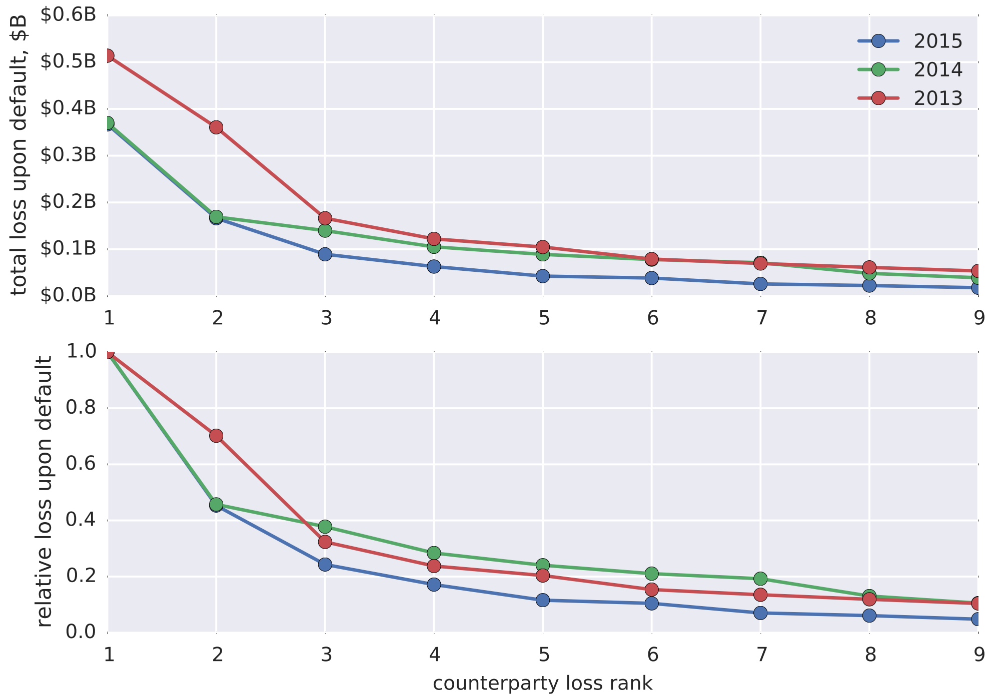
$$\begin{gathered} (p_1, p_2, ..., p_n) \\ where\ \Delta V_{p_1}^{bhc} \geq \Delta V_{p_2}^{bhc} \geq ... \geq \Delta V_{p_n}^{bhc} \\ and\ \Delta V_{p_i}^{bhc} > 0 \end{gathered} \tag{12}$$

Using this description, the BHC's *loss ratio* to counterparty p_i is given as the ratio of foregone gains under p_i's default relative to the same for the BHC's largest counterparty p_1:

$$direct\ loss(p_i) = \Delta V_{p_i}^{bhc} / \Delta V_{p_1}^{bhc} \tag{13}$$

Figure 3 describes $\Delta V_{p_i}^{bhc}$ over decreasing BHC counterparty rank i in the top panel and $direct\ loss(p_i)$ over i in the bottom panel. Losses decline over time: for correspondingly-ranked counterparties, losses in 2015 were lower than they were in 2013. Second, loss magnitudes are small relative to those realized in the financial crisis. Finally, the exercise reveals the granular nature of BHC counterparty portfolios. The first and second largest counterparties are considerably more consequential to the trading book than subsequent counterparties. The results pertain to the CDS market, which may not describe a bank's total counterparty credit derivative portfolio. While the results support CCAR's focus on the impact of the BHC's largest counterparty, as we shall subsequently show, other impacts may be larger.

Figure 3: Size and Proportion of Average BHC's Direct Losses from Counterparty Default



Source: Authors' calculations using DTCC data

6.2 Firm-Level Indirect Impacts

BHCs may also realize indirect losses of a counterparty's failure through strains realized on other market participants. Specifically, counterparty p may face other BHC counterparties and upon failure, impose losses upon them. Impacted counterparties may be constrained in ways which limit their ability to meet obligations to the BHC. As an example, the BHC's counterparties may be unable to post adequate margin or collateral of suitable quality. Consequently, the network impact of a counterparty failure may be amplified when it results in successive failures of other counterparties, the total losses of which may exceed the capacity of a BHC to withstand.

We consider indirect losses that arise from a BHC counterparty's default:

$$\Delta V_{p_i}^{CP(bhc)} = \sum_{\substack{q \in \\ CP(bhc), \\ q \neq p_i}} max(\Delta V_{p_i}^{q}, 0) \tag{14}$$

where $CP(bhc)$ is the set of all counterparties to a BHC and $\Delta V_{p_i}^{q}$ is analagous to the definition in Equation 11 but rather concerns BHC counterparty q rather than the BHC directly. The *indirect loss* ratio is given as the total losses realized by the BHC's remaining counterparties to the failure of the BHC's largest counterparty:

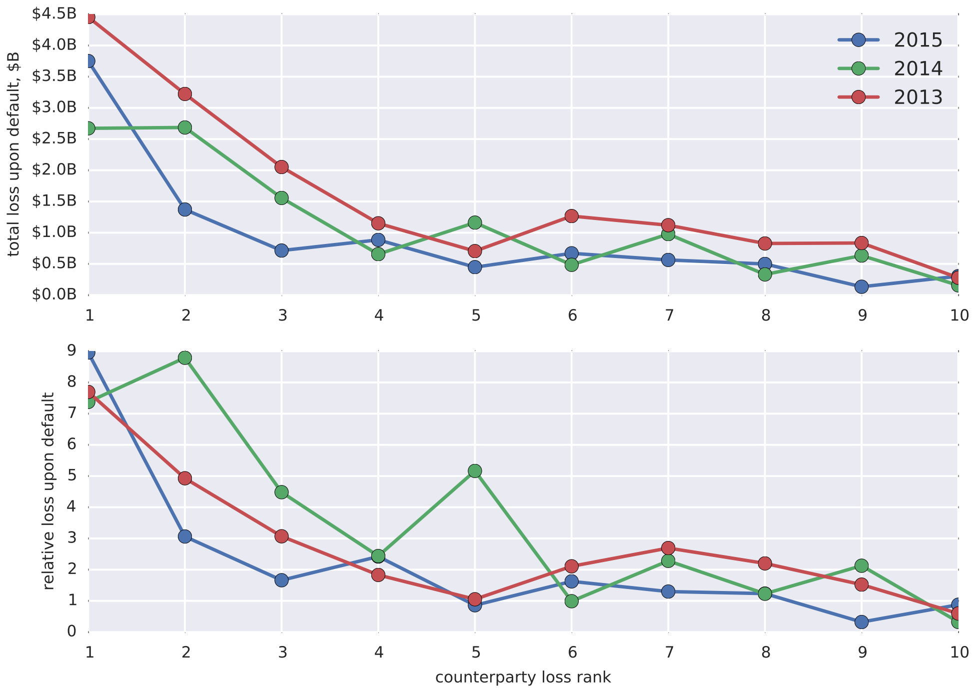
$$indirect\ loss(p_i) = \Delta V_{p_i}^{CP(bhc)} / \Delta V_{p_1}^{bhc} \tag{15}$$

The profile of $\Delta V_{p_i}^{CP(bhc)}$ over decreasing largest counterparty rank i is plotted in the top panel of Figure 4, and the profile of the ratio $indirect\ loss(p_i)$ is plotted below. The losses realized by the network of a BHC's remaining counterparties to it's largest counterparty failure are much larger in absolute terms than the losses realized solely by the BHC in Figure 3. The losses attributable to the largest counterparties are much larger to the network than for smaller counterparties, just as is the case for direct losses realized by BHCs. However, the network importance of subsequent counterparties is not monotonically decreasing as is the case for direct impacts.

This work yields two important findings. First, we show that the indirect effect of the largest counterparty's failure on the bank's other counterparties in many cases would be material under the stress test assumptions. For example, in Figure 4, one can observe that BHC counterparty network losses from a failure of the BHC's single largest counterparty on average is nearly nine times greater than those of the BHC's own losses from its single largest counterparties' failure. Thus, consideration of a large BHC counterparty failure that does not take into account second-order effects is likely to significantly understate potential risk to the BHC.

Second, we find instances where the failure of smaller counterparties would place greater stress

Figure 4: Size and Proportion of Average BHC's Indirect Losses from Counterparty Default



Source: Authors' calculations using DTCC data

Table 8: Direct and Indirect Losses for Counterparty-Stressed Bank Holding Companies in 2014

eth largest counterparty default	Ratio	BHC$_1$	BHC$_2$	BHC$_3$	BHC$_4$	BHC$_5$
	BHC Direct Loss (b,1):	1.00	1.00	1.00	1.00	1.00
1	BHC Indirect Loss (b,1):	5.22	4.52	10.2	9.14	7.70
	BHC Direct Loss (b,2):	0.52	0.19	0.86	0.87	0.63
2	BHC Indirect Loss (b,2):	4.06	2.85	7.65	19.0	10.3
	BHC Direct Loss (b,3):	0.33	0.15	0.75	0.87	0.58
3	BHC Indirect Loss (b,3):	3.02	2.17	2.44	11.7	3.03
	BHC Direct Loss (b,4):	0.12	0.14	0.74	0.71	0.38
4	BHC Indirect Loss (b,4):	0.36	0.63	5.15	2.67	3.34

Note: For the purposes of anonymity we present only five of the six BHCs.
Source: Authors' calculations using DTCC data

on the BHC's remaining counterparty network than failure of the BHC's largest counterparty. For example, consider Table 8, where BHC 4's second- and third-largest counterparties each transmit a smaller loss than BHC 4's largest counterparty. However, BHC 4's remaining counterparty network would incur greater losses from the failure of BHC 4's second- or third-largest counterparty than from the failure of BHC 4's largest counterparty. Another example of this phenomenon is BHC 5's second-largest counterparty in 2014. These observations underscore the importance of the network in evaluation of the most impactful BHC counterparties under stress.

6.3 Core Systemic Impacts

Supervisory concern focuses on firm-level solvency but places less emphasis on risks to the system. While CCAR has a useful microprudential focus, it may not take into account systemic consequences to the six banks covered by the CCAR trading shock. We refer collectively to these banks as being in the *core* financial system. The resilience of the core may be overstated in systemic stresses. In particular, shared counterparties may pose large risks to the core even if they are not the most significant on a firm-by-firm basis. Large and collectively shared counterparties, under stress, may concurrently transmit shocks to banks in the core. By identifying the largest collectively shared, or largest core counterparties, one may better differentiate systemic from firm-specific risks. To measure the difference between microprudential and macroprudential stress testing, we evaluate concentration risk under both approaches.

We construct two Herfindahl measures, the first for BHC counterparty concentrations and the second for core counterparty concentrations. The Herfindahl measure of a bank's counterparty portfolio is the counterparty i's share of total owed variation margin payments under stress, s_i^{bhc}.

$$\begin{gathered} s_i^{bhc} = \Delta V_i^{bhc} / \sum_p^P \Delta V_p^{bhc} \\ where\ \Delta V_p^{bhc} > 0\ \forall\ p \end{gathered} \tag{16}$$

The Herfindahl concentration measure readily follows:

$$H^{bhc} = \sum_{i=1}^{N} s_i^{bhc^2} \tag{17}$$

By contrast, a more macroprudential approach evaluates the value of a non-core counterparty p to the core network. We define the measure as

$$\Delta V_p^{core} = \sum_{\substack{bhc_i \in \\ core}} \left\{ \sum_{\substack{j \in \\ Sales}} \Delta MtM_j^{bhc_i \to p} + \sum_{\substack{k \in \\ Purchases}} \Delta MtM_k^{p \to bhc_i} \right\} \tag{18}$$

A corresponding share of non-core counterparty i's share of total owed variation margin payments under stress follows:

$$\begin{gathered} s_i^{core} = \Delta V_i^{core} / \sum_p^P \Delta V_p^{core} \\ where\ \Delta V_p^{core} > 0\ \forall\ p \end{gathered} \tag{19}$$

The core financial system Herfindahl concentration measure is defined as

$$H^{core} = \sum_{i=1}^{M} s_{i,core}^2 \tag{20}$$

In Tables 9, 10, and 11 BHC and core financial system concentration measures are reported for each CCAR scenario. BHC Herfindahl measures vary between 2013 and 2015, and the composite BHC Herfindahl increases from 1026 (2013) to 1592 (2015). However, the Herfindahl measure of the core increases from 562 (2013) to 2882 (2015). For the core, or the six banks subject to the CCAR trading shock, this is equivalent to an effective reduction from 17.7 to 3.5 counterparties over this horizon. Further, concentration lies substantially in the largest counterparty to the core. Thus, the BHC or microprudential measure of concentration shows less evidence of risk than a macroprudential measure which considers the collective risks to the core.

[Table 9] [Table 10] [Table 11]

A comparison between BHC and core Herfindahl measures suggests that focus on bank-level solvency may not inform systemic risk concerns. A BHC may be able to manage the failure of its largest counterparty when other BHCs do not concurrently realize losses from the same counterparty's failure. However, when a shared counterparty fails, banks may experience additional stress. The financial system is much more concentrated to (and firms' risk management is less prepared for) the failure of the system's largest counterparty. Thus, the impact of a material counterparty's failure could affect the core banking system in a manner that CCAR may not fully capture.

Table 12: Average Herfindahl Scores of Individual Bank Holding Companies and Core System Losses

	2013		2014		2015	
	Mean BHC	Core	Mean BHC	Core	Mean BHC	Core
HHI	1026	562	979	704	1592	2882
HHI ex 1st largest CP	822	256	673	523	782	327
HHI ex 1st, 2nd largest CPs	485	233	604	379	597	265
HHI ex $\cdots$, 3rd largest CPs	430	207	530	285	490	242
HHI ex $\cdots$, 4th largest CPs	396	204	479	252	385	224
HHI ex $\cdots$, 5th largest CPs	358	199	436	236	350	197

Source: Authors' calculations using DTCC data

6.4 Peripheral Systemic Impacts

We evaluate the *periphery's* collective losses to the core's largest counterparties in this section. Here we seek to widen further the macroprudential lens. Specifically, we consider not just the effect on the core from its largest counterparties, but also the impact of these important counterparties on the periphery. The goal of this exercise is to arrive at a view of indirect risks the periphery could pose to the core if the core realized counterparty risk:

$$\Delta V_p^{periphery} = \sum_{\substack{q\in \\ periphery, q\neq p}} max\left(\Delta V_p^q, 0\right) \tag{21}$$

where *periphery* is the set of all non-BHC counterparties to the core financial system and ΔV_p^q is defined as before. The *peripheral loss ratio* is given as the total losses realized by the peripheral financial system to the failure of the core financial system's largest counterparty:

$$peripheral\ loss(p_i) = \Delta V_{p_i}^{periphery} / \Delta V_{p_1}^{core} \tag{22}$$

The peripheral concentration measure is analagous to the core measure:

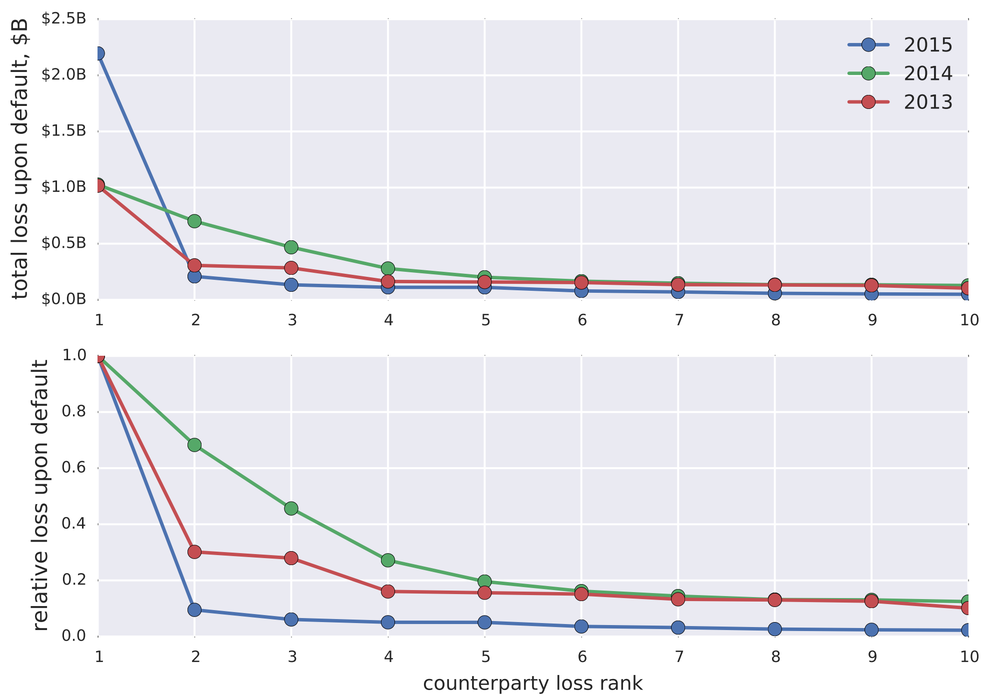
$$\begin{gathered} s_i^{periphery} = \Delta V_i^{periphery} / \sum_p^P \Delta V_p^{periphery} \\ where\ \Delta V_p^{periphery} > 0\ \forall\ p \end{gathered} \tag{23}$$

The peripheral financial system's Herfindahl concentration measure is

$$H^{periphery} = \sum_{i=1}^{M} s_{i,periphery}^2 \tag{24}$$

The profile of $\Delta V_{p_i}^{periphery}$ over decreasing largest counterparty rank i is plotted in the top panel of Figure 6, and the profile of the ratio $peripheral\ loss(p_i)$ is plotted below. Of note, the losses realized by the periphery are larger than the losses to be realized by the core system for all CCAR years, except for the most recent year, 2015 (see lower panels of Figures 5 and 6). This is an interesting result because we are evaluating the losses of the periphery based on the core's largest counterparties. Thus, in 2013 and 2014 the periphery's strain would have exceeded those of the six BHCs.

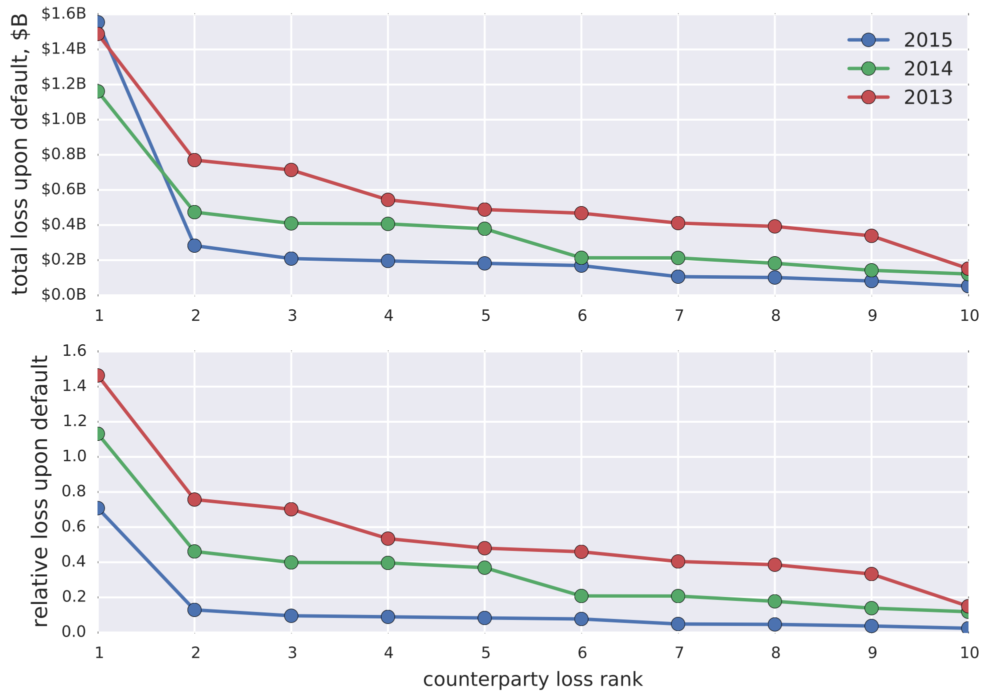
Figure 5: Size and Proportion of Core Losses from Default of Core's Counterparties



Source: Authors' calculations using DTCC data

From Table 13 we can observe that the periphery's concentrations in the core's largest counterparty have substantially increased in the most recent CCAR year. The periphery's effective

Figure 6: Size and Proportion of Peripheral Losses from Default of Core's Counterparties



Source: Authors' calculations using DTCC data

concentration has increased from approximately 11 firms to just over 5.

These findings illustrate that the losses to the periphery are larger (in absolute terms) than losses of the core's largest counterparty. While individual BHCs' direct losses are declining over subsequent CCAR stress tests, counterparty credit risks to the banking system collectively have risen and may suggest a greater systemic risk than is commonly understood.

Table 13: Herfindahl Scores for Peripheral System Losses

	2013 Peripheral System	2014 Peripheral System	2015 Peripheral System
HHI	826	895	1866
HHI ex 1st largest CP	669	613	539
HHI ex 1st, 2nd largest CPs	664	602	498
HHI ex $\cdots$, 3rd largest CPs	640	590	481
HHI ex $\cdots$, 4th largest CPs	639	543	451
HHI ex $\cdots$, 5th largest CPs	634	450	403

Source: Authors' calculations using DTCC data

7 Conclusion

This paper highlights the microprudential premise and limited view of systemic risk in supervisory stress tests. We find, using the network of counterparty exposures in the credit derivatives market, that CCAR's focus on the largest counterparty default risk at an individual BHC is a suitable starting proxy for knowledge of the full CDS network. However, losses arising from the failure of a BHC's largest counterparty do not comprise the entirety of losses. The failure, in turn, can stress other BHC counterparties. Furthermore, larger counterparty concentrations (in proportion and magnitude) exist for the core financial system than for individual firms within it. Incorporation of a macroprudential perspective in stress tests would inform supervisors and regulators of risks that may not be studied and may be greater than those which are commonly understood.

Three key contributions flow from this work. Our study suggests material differences between the concentration of firms' largest counterparties individually and systemically. As banks understandably have limited awareness of the full CDS network, this has real-world implications for the efficacy of banks' and other financial firms' counterparty risk management in stress. Specifically, firms' counterparty hedging strategies are unlikely to be sufficient to cope with systemically important counterparties. Second, this study highlights the importance of robust data collection and analysis by regulators. Systemic concentration risks are not possible to infer when supervisors examine bilateral exposures that lack granular data such as contract details. Finally, supervisors must also have the capacity to compute market loss analagous to that which would actually be realized under stress. It is not certain that current data collections and analysis extend beyond analysis of gross and net notional volumes, which do not inform economic loss.

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Table 2: 2013 CCAR Severely Adverse Market Shocks

Corporate Credit							
Advanced Economies							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (%)	67.12	67.12	106.60	201.71	138.77	124.43	124.43
Emerging Markets							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (%)	132.89	132.89	132.89	132.89	199.60	421.12	421.12

Loan							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Relative MV Shock (%)	-22.60	-22.60	-22.60	-22.60	-26.87	-30.47	-39.81

Eurozone Advanced Economy Bank Corporate Credit							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (%)	100.01	100.01	119.75	167.30	169.18	272.78	272.78

Periphery Eurozone Bank Corporate Credit							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (%)	132.89	132.89	132.89	132.89	199.60	421.12	421.12

State & Municipal							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (bps)	2	18	86	222	222	222	222

Note: For Sovereign & Supra values see Federal Reserve worksheet, "CCAR-2013-Severely-Adverse-Market-Shocks-data."
Source: Federal Reserve

Table 3: 2014 CCAR Severely Adverse Market Shocks

Corporate Credit							
Advanced Economies							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (%)	75.4	75.4	128.7	250.1	205.2	223.3	223.3
Emerging Markets							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (%)	158.8	181.5	204.2	235.1	405.8	412.7	440.8

Loan							
Advanced Economies							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Relative MV Shock (%)	-22.6	-22.6	-22.6	-22.6	-26.9	-30.5	-39.8
Emerging Markets							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Relative MV Shock (%)	-33.9	-33.9	-33.9	-33.9	-40.4	-45.8	-59.0

Periphery Eurozone Corporate Credit							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (%)	350.6	215.7	205.4	215.9	429.3	540.0	540.0

Periphery Eurozone Loan							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Relative MV Shock (%)	-33.9	-33.9	-33.9	-33.9	-40.3	-45.7	-59.7

State & Municipal Credit							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (bps)	3	23	107	277	277	277	277

Note: For Sovereign & Supra values see Federal Reserve worksheet,
"CCAR-2014-Severely-Adverse-Market-Shocks-data."
Source: Federal Reserve

Table 4: 2015 CCAR Severely Adverse Market Shocks

Corporate Credit							
Advanced Economies							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (%)	130.0	133.0	110.2	201.7	269.0	265.1	265.1
Emerging Markets							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (%)	191.6	217.2	242.8	277.5	401.9	436.4	465.8

Loan							
Advanced Economies							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Relative MV Shock (%)	-6.2	-6.7	-13.4	-22.6	-26.9	-30.5	-39.8
Emerging Markets							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Relative MV Shock (%)	-23.2	-27.6	-32.0	-36.4	-61.3	-66.7	-72.2

State & Municipal Credit							
	AAA	AA	A	BBB	BB	B	<B or Not Rated
Spread Widening (bps)	12	17	37	158	236	315	393

Note: For Sovereign & Supra values see Federal Reserve worksheet, "CCAR-2015-Severely-Adverse-Market-Shocks-data.".
Source: Federal Reserve

Table 5: Gross Profits and Losses by Sector

Corporate Investment Grade: Advanced Economies			
CCAR	Base	Stressed	Change
2013	$746	($645)	($1,390)
2014	$1,271	($1,100)	($2,380)
2015	$1,050	($336)	($1,390)

Corporate Investment Grade: Emerging Markets			
CCAR	Base	Stressed	Change
2013	$82.9	($8.57)	($91.5)
2014	$163	($312)	($474)
2015	$146	($106)	($251)

Corporate Sub Investment Grade: Advanced Economies			
CCAR	Base	Stressed	Change
2013	($88.7)	($1,500)	($1,410)
2014	$240	($712)	($952)
2015	$384	($480)	($864)

Corporate Sub Investment Grade: Emerging Markets			
CCAR	Base	Stressed	Change
2013	$32.4	($91.5)	($124)
2014	$25.9	($128)	($154)
2015	$7.93	($103)	($111)

Sovereign			
CCAR	Base	Stressed	Change
2013	($168)	($360)	($192)
2014	($58.6)	($855)	($797)
2015	($3.48)	($326)	($323)

US Financials			
CCAR	Base	Stressed	Change
2013	($585)	($1,560)	($971)
2014	$312	($172)	($484)
2015	$359	($14.8)	($374)

Non-US Financials			
CCAR	Base	Stressed	Change
2013	($256)	($2,100)	($1,850)
2014	$354	($737)	($1,090)
2015	$775	$135	($640)

Source: Authors' calculations using DTCC data
Note: Results are for yearly CCAR supervisory scenarios from the protection seller's perspective. Corporate Grade categories only includes non-Financials. Presented in $billions.

Table 6: Net Notional Exposures

	CCAR 2013	CCAR 2014	CCAR 2015
Median	($20,000,000)	($21,900,000)	($20,000,000)
Std Dev	$6,350,000,000	$6,780,000,000	$8,190,000,000
Skewness	7	9	20
Kurtosis	136	162	537
Avg BHC/FBO	$2,300,000,000	$1,600,000,000	($1,740,000,000)
Avg Non-BHC/FBO	($61,100,000)	($47,100,000)	$49,300,000

Net Notional Exposure Distribution			
Percentile	CCAR 2013	CCAR 2014	CCAR 2015
5	($1,660,000,000)	($1,950,000,000)	($2,210,000,000)
10	($799,000,000)	($902,000,000)	($865,000,000)
20	($275,000,000)	($336,000,000)	($319,000,000)
30	($22,500,000)	($130,000,000)	($130,000,000)
40	($50,000,000)	($64,500,000)	($50,000,000)
50	($20,000,000)	($21,900,000)	($20,000,000)
60	($6,360,000)	($8,100,000)	($5,000,000)
70	$2,940,000	$0	$2,220,000
80	$43,000,000	$27,100,000	$41,900,000
90	$262,000,000	$227,000,000	$258,000,000
95	$889,000,000	$836,000,000	$835,000,000

Note: Positive dollars values represent net CDS exposure sold, negative dollars values represent net CDS exposure bought.
Source: Authors' calculations using DTCC data

Table 7: Stressed Profits and Losses

	CCAR 2013	CCAR 2014	CCAR 2015
Median	\$602,000	\$854,000	\$533,000
Std Dev	\$262,000,000	\$230,000,000	\$236,000,000
Skewness	-15	-9	-22
Kurtosis	330	186	614
Avg BHC/FBO	(\$280,000,000)	(\$156,000,000)	(\$45,000,000)
Avg Non-BHC/FBO	\$8,000,000	\$4,690,000	\$1,640,000

Net CCAR Stressed P&L ΔDistribution			
Percentile	CCAR 2013	CCAR 2014	CCAR 2015
5	(\$31,200,000)	(\$43,200,000)	(\$26,200,000)
10	(\$8,480,000)	(\$9,610,000)	(\$13,400,000)
20	(\$1,450,000)	(\$1,100,000)	(\$1,140,000)
30	(\$33,600)		(\$67,800)
40	\$138,000	\$207,000	\$65,100
50	\$602,000	\$854,000	\$533,000
60	\$1,740,000	\$2,180,000	\$1,510,000
70	\$4,470,000	\$5,230,156	\$4,180,000
80	\$10,800,000	\$12,700,000	\$10,500,000
90	\$32,300,000	\$36,000,000	\$31,300,000
95	\$78,600,000	\$80,700,000	\$79,700,000

Note: Values represent dollar change relative to baseline marks.
Source: Authors' calculations using DTCC data

Table 9: Individual and Core Herfindahl Concentration for Counterparty-Stressed Bank Holding Companies in 2013

	BHC_1	BHC_2	BHC_3	BHC_4	BHC_5	Mean BHC	Core
HHI	1434	629	921	714	1431	1026	562
HHI ex 1st largest CP	1310	515	610	304	1369	822	256
HHI ex 1st, 2nd largest CPs	676	468	533	300	447	485	233
HHI ex $\cdots$, 3rd largest CPs	618	456	387	294	394	430	207
HHI ex $\cdots$, 4th largest CPs	541	455	362	289	333	396	204
HHI ex $\cdots$, 5th largest CPs	391	460	332	284	321	358	199

Note: For the purposes of anonymity we present only five of the six BHCs.
Source: Authors' calculations using DTCC data

Table 10: Individual and Core Herfindahl Concentration for Counterparty-Stressed Bank Holding Companies in 2014

	BHC_1	BHC_2	BHC_3	BHC_4	BHC_5	Mean BHC	Core
HHI	851	1459	558	1344	681	979	704
HHI ex 1st largest CP	845	515	555	872	580	673	523
HHI ex 1st, 2nd largest CPs	826	502	553	592	549	604	379
HHI ex $\cdots$, 3rd largest CPs	778	501	529	350	493	530	285
HHI ex $\cdots$, 4th largest CPs	577	493	514	332	481	479	252
HHI ex $\cdots$, 5th largest CPs	438	482	472	332	455	436	236

Note: For the purposes of anonymity we present only five of the six BHCs.
Source: Authors' calculations using DTCC data

Table 11: Individual and Core Herfindahl Concentration for Counterparty-Stressed Bank Holding Companies in 2015

	BHC_1	BHC_2	BHC_3	BHC_4	BHC_5	Mean BHC	Core
HHI	1450	1433	1462	2217	1398	1592	2882
HHI ex 1st largest CP	725	862	377	949	997	782	327
HHI ex 1st, 2nd largest CPs	686	824	344	477	652	597	265
HHI ex $\cdots$, 3rd largest CPs	547	725	306	297	575	490	242
HHI ex $\cdots$, 4th largest CPs	424	388	288	291	536	385	224
HHI ex $\cdots$, 5th largest CPs	410	340	255	285	461	350	197

Note: For the purposes of anonymity we present only five of the six BHCs.
Source: Authors' calculations using DTCC data